Computer-aided diagnosis of different rotator cuff lesions using shoulder musculoskeletal ultrasound

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Abstract

The lifetime prevalence of shoulder pain approaches 70%, which is mostly attributable to rotator cuff lesions such as inflammation, calcific tendinitis, and tears. On clinical examination, shoulder ultrasound is recommended to detect lesions. However, inter-operator variability of diagnostic accuracy exists due to the operator' experience and expertise. In this study, a computer-aided diagnosis (CAD) system was developed to assist ultrasound operators in diagnosing rotator cuff lesions and to improve practicality of ultrasound examination. The collected cases included 43 inflammations, 30 calcific tendinitis, and 26 tears. For each case, the lesion area and texture features were extracted from the entire lesions and combined in a multinomial logistic regression classifier for lesion classification. The proposed CAD achieved an accuracy of 87.9%. The individual accuracy of this CAD system was 88.4% for inflammation, 83.3% for calcific tendinitis, and 92.3% for tear groups. The *k* value of Cohen's Kappa was 0.798. Based on diagnostic performance, this CAD has promise for clinical use.

Keywords: Rotator cuff lesions, shoulder ultrasound, computer-aided diagnosis, texture

Introduction

The prevalence of shoulder pain is high in many countries, and the lifetime prevalence of shoulder pain approaches 70% (Luime et al. 2004), only lower than lower back pain prevalence (84%) (Walker 2000). In America, shoulder pain costs the health care system 7 billion per year and is the cause of 13% of sick leave (Hidalgo-Lozano et al. 2010). Up to 70% of shoulder pain is attributed to rotator cuff lesions (Macfarlane et al. 1998; Mitchell et al. 2005). According to Neer's classification system, lesions of the rotator cuff can be classified as inflammation, calcific tendinitis, and full or partial thickness tears. Inflammation is thickened, irregular, heteroechoic and loss of homogeneous texture with no signs of tears. Calcific tendinitis comes in several forms, and foci of hyperechoic micro-calcification without acoustic shadows are the common form. However, large foci of calcification may be soft or hard, solitary or lobulated (Beggs 2011). Soft calcification is fragmented and hyperechoic with a well-defined margin and with or without acoustic shadows. Hard calcification has a hyperechoic convex superficial contour, often with acoustic shadows (Beggs 2011). On ultrasound, supraspinatus tears appear as hypoechoic areas with irregular margins (Kurol et al. 1991; Allen and Wilson 2001; Vlychou et al. 2009). They could extend from the bursal to the articular surface as full-thickness tears or affect only a part of tendon thickness as the partial-thickness tears (Beggs 2011).

Patients with rotator cuff lesions have shoulder pain, positive impingement signs, limited forward elevation, weak abduction, and external rotation, which may cause difficulty in holding things. Rotator cuff tears, with an overall prevalence rate of 20.7%, are the most severe type, causing severe shoulder pain and impingement signs, limited forward elevation and weak abduction and external rotation. As the population ages, the prevalence rate of rotator cuff tears is expected to increase.

In the treatment of rotator cuff tendinopathy, the status of rotator cuff integrity determines surgical intervention or conservative treatment. Clinical symptoms and physical examination are considered unreliable to diagnose rotator cuff lesions (Park et al. 2005) because the severity of the rotator cuff tendinopathy affects the diagnostic values of commonly used clinical tests. Additionally, considerable inter-observer variability exists between physicians (Beaudreuil et al. 2009). Consequently, clinical assessment relies on imaging modalities to evaluate the integrity of rotator cuff tendons (Murphy et al. 2013). Shoulder X-ray, ultrasound, magnetic resonance imaging and more specific arthrography are available imaging techniques for clinical examination (Shahabpour et al. 2008). The literature recommends shoulder ultrasound as a useful imaging tool to detect rotator cuff lesions (Allen and Wilson 2001; Middleton et al. 2004; de Jesus et al. 2009) and full-thickness rotator cuff tears when performed by experienced musculoskeletal radiologists or shoulder orthopedic surgeons (Smith et al.

2011). The accuracy of ultrasound performed by experienced operators is comparable to that of magnetic resonance imaging (MRI) (Teefey et al. 2004; de Jesus et al. 2009). The diagnostic performance based on ultrasound is likely reduced upon examination by general radiologists and ultrasonographers as well as to identify partial-thickness rotator cuff tears and other intra-substance tendon abnormalities (Smith et al. 2011). To strengthen the clinical use of ultrasound, the inter-operator variability should be further reduced.

Ultrasound is a useful diagnostic tool for shoulder disorders and as an initial imaging study for detecting rotator cuff lesions. The advantages of ultrasound to detect shoulder lesions are that it is quick, relatively inexpensive, easy to assess and with few contraindications (Beggs 2006). Most publications of shoulder ultrasound studies demonstrate the sensitivity and specificity of rotator cuff tears. The accuracy of shoulder ultrasound to detect partial and full rotator cuff tears has a sensitivity of 46% to 95% and a specificity of 50% to 97% (Mack et al. 1985; Brandt et al. 1989; Soble et al. 1989; Kurol et al. 1991; Wiener and Seitz 1993; van Holsbeeck et al. 1995; Alasaarela et al. 1998; Read and Perko 1998; Teefey et al. 2000; Roberts et al. 2001; Miller et al. 2008). Sensitivity and specificity for the assessment of full thickness rotator cuff tears are better than for partial-thickness rotator cuff tears (Middleton et al. 2004; Teefey et al. 2004; Smith et al. 2011). The use of ultrasound for the assessment of partial-thickness rotator cuff tears is controversial (Martin-Hervas et al. 2001; Mitchell et al. 2005; Moosmayer et al. 2007) and is an uncertain clinical issue. According to the literature reviews, the inter-observer agreement of rotator cuff lesions from shoulder ultrasound is only poor to moderate due to different operator professionals and experiences (Kamwendo et al. 1991; de Winter et al. 1999; O'Connor et al. 2005), which implies that additional diagnostic tools such as Computer-aided diagnosis (CAD) are needed for less experienced general and junior operators.

CAD systems have been proposed to distinguish between benign and malignant lesions such as breast, prostate cancer (Joo et al. 2004; Doi 2005; Giger et al. 2008; Moon et al. 2012a; Lo et al. 2015a; Lo et al. 2015b) and the identification of carotid atherosclerosis (Bonanno et al. 2015). The advantages of CAD systems include quantitative attributes, efficiency, and consistency. After extracting the quantitative features from a lesion area, the complementary abilities of various features are combined in an artificial intelligence classifier to estimate the likelihood of a specific type of lesion. With the assistance of CAD, the diagnostic performance of seven radiologists in distinguishing between benign and malignant breast lesions was improved (Kashikura et al. 2013). However, few studies addressed the application of CAD in shoulder musculoskeletal ultrasound. One study used a fixed rectangular to enclose region of interest (ROI) for feature extraction which may not reveal the properties of whole lesion tissue. (Horng and Chen 2009).

The purpose of this study is to create a CAD system using shoulder musculoskeletal ultrasound to improve operators' performance in diagnosing rotator cuff lesions. It could be the diagnostic tool to assist the general radiologists and ultrasonographers in shoulder musculoskeletal ultrasound and to improve practicality of shoulder ultrasound examination. Based on the success of CAD systems in interpreting ultrasound images, a CAD system based on shoulder ultrasound was proposed in this study to classify rotator cuff lesions as inflammation, calcific tendinitis, and thickness tears. Numerous textural features and lesion area were implemented in the experiment to diagnose rotator cuff lesions. To the best of our knowledge, this is the first study exploring the performance of quantitative features extracted from whole rotator cuff lesions in shoulder ultrasound for lesion classification. The results would be especially helpful to assist junior physicians in distinguishing lesions with similar properties on clinical examination.

Materials and Methods

Patients and data acquisition

Institutional review board approval was obtained and informed consent was waived for this retrospective study. The database consisted of 99 shoulder ultrasound images in 93 adult patients collected from January 2011 to February 2014. The 93 patients consisted of 43 men and 50 women aged 31-89 years (mean age, 57.5 years).

The shoulder ultrasound images in the collected database were generated using an ALOKA alpha-6 ultrasound scanner (Hitachi-Aloka Medical, Tokyo, Japan) with a linear array probe (scan width: 36 mm) ranging from 5 to 13 MHz. The settings of the ultrasound scanner, such as gain compensation, were consistent for all patients. During examination, the patients were in a standard sitting position and the routine of ultrasound examination was followed. After acquisition, the shoulder ultrasound images were removed from the scanner and stored as 8-bit images with pixel values ranging from 0 to 255. The lesion types were classified into three categories, including 43 cases of tendon inflammation, 30 cases of calcific tendinitis, and 26 cases of supraspinatus tear. The diagnosis determined by the consensus of one shoulder orthopedic surgeon and one physical medicine and rehabilitation (PM&R) physician was used as the gold standard to evaluate the performance of the proposed CAD system.

Contour delineation

The proposed CAD was a semi-automatic procedure based on the input of manually delineated lesion contours. The lesion contours were manually delineated by a shoulder orthopedic surgeon using ImageJ, a medical image processing program developed at the NIH by Wayne Rasband (http://rsb.info.nih.gov/ij/). The principle of the delineation procedure was to enclose the lesion area while avoiding the normal tendons. Fig. 1 shows the acquired ultrasound images and the delineation of lesion contours based on the sonographic appearance. The shoulder orthopedic surgeon involved in identifying the lesion contour and the one whose judgment formed the gold standard were one and the same.

Feature extraction

Using the sonographic appearance, the lesion contours that enclosed the specific tissue were obtained after the contour delineation. From the lesions, the lesion area and texture features were extracted to express tissue characteristics. The normal supraspinatus tendon is a convex beak-shaped hyperechoic structure in long-axis view (Petranova et al. 2012). The features of supraspinatus inflammation are heteroechoic and loss of homogeneous texture with no signs of tears. Foci of hyperechoic micro-calcification without acoustic shadows are the common form of calcific tendinitis. However, large foci of hard calcification appear hyperechoic convex contour with acoustic shadows (Beggs 2011). Supraspinatus tears appear as hypoechoic areas with irregular margins (Kurol et al. 1991; Allen and Wilson 2001; Vlychou et al. 2009).

According to the tissue characteristics mentioned in prior studies, the morphological features widely used in CAD systems may not be useful in lesion classification because there is no rule of shape description for a specific lesion type. Morphology features in CAD systems focus on dealing with the form and structure of a lesion such as the outward appearance. Nevertheless, the lesion area is a basic property that can be combined with other features for classification. In the experiment, the number of pixels included in the delineated lesion was counted and used as an estimate of the lesion area.

To quantify the echogenicities of different lesion types, the second-order statistics of ultrasound texture (Moon et al. 2012b) are proposed in this study as quantitative texture features. Second-order statistics describes the correlations between adjacent pixels in the lesion area. In ultrasound images, texture patterns are the combinations of tissue echogenicities expressed on a gray-scale. Consequently, analyzing the gray-scale co-occurrence matrices (GLCM) (Haralick et al. 1973) representing the correlations between adjacent pixels is proposed to reveal the texture difference between various lesion types.

In GLCM, an image can be quantized to be *G* with a reduced number of intensity bins, N_g (N_g=64 in the experiment). A new image G having less image values can be obtained with a reduced number of intensity bins. Lower levels than 64 had relatively poor performance in the experiment while more levels induced extra computation.

Considering the efficiency and enough details of levels, 64 quantization levels were used. Afterward, the $N_g \times N_g$ co-occurrence matrices $P=[p(i,j|d,\theta)]$ were generated from G by scanning each image pixel and its neighboring pixels. The element $P=[p(i,j|d,\theta)]$ indicates the frequencies of two neighboring pixel values separated by distance d and the direction angle θ; one has a gray value i and the other has a gray value j. Fig. 2 shows the two parameters d=1 and θ=0°, 45°, 90°, or 135° used in the GLCM method for the relationship among neighboring pixels in the experiment. Four co-occurrence matrices with different angles were considered to extract GLCM features.

Eight GLCM texture features were calculated based on the following formulas:

Energy:
$$f_1 = \sum_i \sum_j p(i, j|d, \theta)^2 \tag{1}$$

Entropy:
$$f_2 = -\sum_i \sum_j p(i, j|d, \theta)\log\left(p(i, j|d, \theta)\right) \tag{2}$$

Correlation:
$$f_3 = \frac{\sum_i \sum_j (i-\mu_x)(j-\mu_y)p(i, j|d, \theta)}{\sigma_x \sigma_y} \tag{3}$$

Local Homogeneity:
$$f_4 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i, j|d, \theta) \tag{4}$$

Inertia:
$$f_5 = \sum_i \sum_j (i-j)^2 p(i, j|d, \theta) \tag{5}$$

Cluster Shade:
$$f_6 = \sum_i \sum_j (i+j-\mu_x-\mu_y)^3 p(i, j|d, \theta) \tag{6}$$

Cluster Prominence:
$$f_7 = \sum_i \sum_j (i+j-\mu_x-\mu_y)^4 p(i, j|d, \theta) \tag{7}$$

Haralick's Correlation:

$$f_8 = \frac{\sum_i \sum_j (i \cdot j) p(i, j|d, \theta) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{8}$$

where μ_x, μ_y, σ_x and σ_y are mean and standard deviation (SD) of the marginal distributions of $p(i,j|d,\theta)$

$$\mu_x = \sum_i i \sum_j p(i, j|d, \theta), \mu_y = \sum_j j \sum_i p(i, j|d, \theta) \tag{9}$$

$$\sigma_x^2 = \sum_i (i - \mu_x)^2 \sum_j p(i, j|d, \theta), \sigma_y^2 = \sum_j (j - \mu_y)^2 \sum_i p(i, j|d, \theta) \tag{10}$$

Because 4 different directions were used in GLCM texture extraction, the mean and SD metrics were the statistics of the 4 directions. Consequently, the mean and SD of the above features were used to present lesion characteristics such as brightness, relative contrast, and heterogeneity for lesion classification.

Statistical analysis

For lesion classification, all the proposed features were combined in a multinomial logistic regression classifier (Hosmer et al. 2000) to establish a prediction model. Stepwise backward elimination was used to explore the most relevant combination of the subset features. When the least error rate was achieved, the corresponding subset features were selected for the prediction model. Leave-one-out cross-validation (Hosmer et al. 2000) was then used to evaluate the generalization ability of the established model. In each iteration, one case was picked from K collected cases and was used to test the trained model by the remaining K-1 cases.

Taking the diagnosis determined by agreement of a shoulder orthopedic surgeon and one physical medicine and rehabilitation physician as the gold standard, the classification performance of the prediction model was obtained by probabilities. For each case, the likelihood of inflammation, calcific tendinitis, and tears was generated and expressed as probabilities. The highest probability value determined the lesion type of the case in the prediction model. The accuracy was obtained by summarizing the cases that were correctly classified. The test methods used in the experiment were analyzed by SPSS software (version 16 for Windows; SPSS, Chicago, IL, USA).

The measurement of observer reliability was performed to examine the agreement of lesion types between the proposed CAD system and two interpreters. As a statistical measure, Cohen's Kappa (Landis and Koch 1977), which ranges from -1.0 to 1.0, where large numbers indicate better reliability, was used to determine the implementation of CAD in the experiment. The agreement was considered slight if the k value was 0.20; fair if k was between 0.21 to 0.40; moderate if k was between 0.41 to 0.60; substantial if k was between 0.61 to 0.80; and almost perfect if k was between 0.81 to 1.00.

Results

After feature selection, the relevant texture features were selected and combined in the classifier to generate a prediction model. Stepwise backward elimination was used to explore the most relevant combination of the subset features. When the least error rate was achieved, the corresponding subset features were selected for the prediction model. The selected features included *Lesion Area, Local Homogeneity* (SD), *Cluster Shade* (mean), *Cluster Prominence* (mean), *Cluster Prominence* (SD), and *Haralick's Correlation* (mean). The performance of the model is listed as Table 1 and the detailed numbers of correctly classified and misclassified cases are listed Table 2. The CAD system achieved an overall accuracy of 87.9%. The individual accuracy of this CAD system was 88.4% for inflammation, 83.3% for calcific tendinitis, and 92.3% for the tear groups. Fig. 3(a) and 3(b) demonstrate a difficult case from the tear group that was correctly classified by the proposed CAD system.

With respect to the measurement of observer reliability between the proposed CAD system and the agreement of two interpreters, the resulting k value of Cohen's Kappa was 0.798, which is substantial and statistically significant ($p<0.001$).

According to the classification result, the selected GLCM texture features describing the statistics of gray-scale distribution of lesion regions reflected the US image appearance and the underlying physical meaning. Such as that *Homogeneity* is formulated to express whether the echogenicities of tissue were similar which can be referred to that supraspinatus tendinitis are heteroechoic and loss of homogeneous texture. Heteroechoic texture represents inflammation and loss of normal strucual property of supraspinatus. *Cluster shade* and *cluster prominence* are measures of the lack of symmetry in gray-scale distributions which indicate that calcific tendinitis come in foci of hyperechoic calcification. *Lesion area* was a selected feature indicating that calcific tendinitis was tend to be smaller than the other two types because micro-calcifications are common form of calcific tendinitis. *Lesion area* would be a useful feature while being combined with other texture features in the classification of inflammation and tear group.

Discussion

A CAD system based on lesion area and statistical textures was established to interpret tissue echogenicities using shoulder musculoskeletal ultrasound. For distinguishing lesion types, a prediction model built by a logistic regression classifier was generated and evaluated. The performance achieved an overall accuracy of 87.9% to classify rotator cuff inflammation, calcific tendinitis and tears. The individual accuracy of the inflammation and tear groups was relatively higher (88.4% and 92.3%, respectively) and that of the calcific tendinitis group was relatively lower (83.3%). Additionally, Cohen's Kappa, acquired from the analysis of observer reliability between the CAD system and the surgeon, was 0.798, which is a substantial and statistically significant result (p<0.001). A previous study (Horng and Chen 2009) used only a portion of the lesion tissue (fixed 30×60 pixels) for tissue characterization to obtain an accuracy of 92.5%. The reported study used numerous features for classification including the fractal dimension, the texture spectrum, the statistical feature matrix, the texture feature coding method, and the gray-level co-occurrence matrix. While more features may result in better performance, the efficiency should be considered for clinical use. Based on the accuracies reported in the previous study and this study, texture features are useful in classifying rotator cuff lesions. Nevertheless, extracting quantitative features from the whole lesion area as proposed in this study is expected to be more reliable than the extraction from partial area in the previous study. In the observation of tissue composition, heterogeneity is commonly presented. Using an arbitrary region of the lesion to extract lesion features would be too subjective and operator dependent. The variability between different lesions and observers is considerable.

The accuracy of the proposed CAD in the calcific tendinitis group was relatively low (83.3%) and Fig. 3(c) and 3(d) show a misclassified case of calcific tendinitis and its delineated lesion area. Clinically, calcific tendinitis is found as hyperechoic spots or masses in ultrasound. It is believed that ultrasound has a high diagnostic accuracy for calcific tendinitis, although few studies focused on the diagnostic accuracy of calcific tendinitis (Martin-Hervas et al. 2001; Kayser et al. 2005). Nevertheless, the CAD system did not perform comparably to a general radiologist as expected. A possible reason may be the heterogeneity of tissue composing calcific tendinitis. Different ultrasound settings during image acquisition results in the brightness variability which could affect the texture values. The effect would be stronger for heterogeneous tissue. In future experiments, intensity-invariant texture features can be developed to reduce the effect caused by brightness variability. However, if the sonographic characteristics of a lesion can't be described by the selected features, it could not be correctly classified. This would be one of the limitations of both ultrasound imaging and the proposed CAD system. Another limitation is that the lesion contours used in the CAD were manually delineated. A future study will be investigated to automatically detect supraspinatus lesion area. Meanwhile, more experiments will be undertaken in the future to explore the clinical application of the proposed CAD, such as improvements in different observers' interpretations with CAD.

Summarily, the CAD system achieved high accuracy (92.3%) in the tear group including partial or full-thickness tears (Fig. 4(a), 4(b)) by means of the analysis of tissue enclosed in the lesion contour. The performance achieved by quantitative echogenicity texture analysis can provide a clinical suggestion for general radiologists or ultrasonographers who may not achieve an accuracy as high as a shoulder orthopedic surgeon (Smith et al. 2011).

Conclusion

The CAD system based on the statistical textures and lesion area extracted from the shoulder ultrasound images achieved good accuracy in classifying rotator cuff inflammation, calcific tendinitis and tears. The diagnostic suggestions generated by the proposed CAD would be practical and promising for clinical use.

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Figure Captions

Fig. 1 Various lesions in the supraspinatus tendon shown in long-axis ultrasound images. (a) A case of tendon inflammation. (b) A case of calcific tendinitis. (c) A case of supraspinatus tear (lesion contours are delineated with yellow lines using ImageJ). (d), (e), (f) The lesion contours of (a), (b), and (c), respectively, which were delineated by a shoulder orthopedic surgeon using ImageJ.

Fig. 2. The pixel pairs of four directions from the centered pixel (o). Pixel 1 to 4 are the neighboring pixels in the direction of 0°, 45°, 90°, and 135° with d=1, respectively.

Fig. 3 A case of partial-thickness supraspinatus tear correctly classified by the proposed CAD system. (a) The partial-thickness supraspinatus tear with unobvious characteristics in long-axis ultrasound image (hypoechoic area near the tendon insertion indicated by a white arrow). (b) The delineated lesion area of tear for CAD analysis. A case of calcific tendintis which was incorrectly classified to inflammation group by the proposed CAD system. (c) Multiple microcalcifications (white arrow) (d) The delineated lesion of calcific tendinitis for CAD analysis.

Fig. 4 An example showing the difference between a full-thickness and a partial-thickness supraspinatus tear. (a) A full-thickness supraspinatus tear shows the hypoechoic area, which extends from the bursal to the articular surface. (b) A case of partial-thickness tear shows the focal hypoechoic area (white arrow), which affects only a part of the tendon thickness.

Tables

Table 1 The accuracy of the proposed CAD in classifying rotator cuff lesions.

Group	Pathology	Accuracy
I	Inflammation	88.4%
II	Calcific tendinitis	83.3%
III	Tears	92.3%
Overall		87.9%

Table 2 The detailed classification results of the proposed CAD in classifying rotator cuff lesions.

Gold standard / CAD	Inflammation	Calcific tendinitis	Tears	Overall
Inflammation	38	2	3	43
Calcific tendinitis	3	25	2	30
Tears	1	1	24	26